Global Value Chains and Economic Development

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Chapter 3

Do Global Value Chains Enhance Economic Upgrading?

A Long View.

Abstract

Exporting through global value chains (GVCs) has recently been highlighted as a panacea for weak industrialisation trends in the South. We study the long-run effects of GVC participation for a large set of countries between 1970 and 2008. We find strong evidence for the positive effects on productivity growth in the formal manufacturing sector. This effect is stronger when the gap with the global productivity frontier is larger. However, we find no evidence for a positive effect on employment generation. These findings also hold in analyses of sub-sets of countries and industries and are robust to the inclusion of non-manufacturing employment.

This chapter is co-authored with Marcel P. Timmer, and based on Pahl and Timmer (2019a).

3 Do Global Value Chains Enhance Economic Upgrading? A Long View.

3.1 Introduction

Economic development relies on productivity growth driven by a reallocation of labour from less to more productive activities. Traditionally, a key role is attributed to the manufacturing sector, which is argued to provide abundant opportunities for capital intensification, scale and technological change. Many studies have shown that poor countries that caught up did so by starting a long process of industrialisation. Conversely, countries lagging in manufacturing growth or even suffering from deindustrialisation have not been able to increase incomes over a sustained period (de Vries et al. 2015; Haraguchi et al., 2017; McMillan et al, 2014; Rodrik, 2016; Szirmai and Verspagen, 2015).

Exporting through global value chain (GVC) participation has recently been highlighted as a possible panacea for weak industrialisation trends (e.g. Taglioni and Winkler, 2016; World Bank, 2017; 2020). Due to improved information and communication technologies, poor countries can nowadays access global markets by carrying out particular stages in the production process (Baldwin, 2014, 2016). Industrialisation through exporting is thus seen as 'easier' than ever, requiring few capabilities of firms and depending more on a country's macro-economic stability and easy physical access to global markets. It is argued that participating in GVCs can stimulate productivity growth through a myriad of channels. These include benefits from specialisation in core tasks, access to imported inputs, knowledge spillovers from multinationals and pro-competitive effects of global competition (Criscuolo and Timmis, 2017). In a cross-country regression, Rodrik (2013) finds that lagging countries catch up with the world productivity leader in manufacturing, *independent* of country characteristics.

Yet, economic development requires that productivity convergence goes hand in hand with sustained employment growth in the modern sector of the economy. From this perspective, fast productivity growth in manufacturing might be a mixed blessing. Rodrik (2013) advances the hypothesis that firms that participate in GVCs might be successful at absorbing advanced technologies but less so in employing labour. Similarly, Baldwin (2014) suggests that GVCs might facilitate entry into global manufacturing goods markets, initially boosting productivity and employment, but at the same time making industrialisation less meaningful as capability building is not guaranteed and long-run development might be stunted. Rodrik (2018) further argues that the technologies associated with GVC production provide diminishing possibilities of substitution of unskilled labour for other factors of production. Producing for global markets demands increasing levels of precision and adherence to quality standards, which requires more automation and less manual work. This makes it harder for developing countries to put their abundant unskilled labour to use. Furthermore, he stresses that skill-biased technologies, such as robotisation, reduce relative demand for unskilled labour and might ultimately reverse patterns of comparative advantage in manufacturing. This leads to reshoring of off-shored stages to advanced countries in the longer run. As a result, GVC participation of developing countries might benefit a small group of highly productive firms but provide limited opportunities for employment (see also Rodrik, 2014). We will refer to this as the 'mixed-blessing hypothesis' of GVC participation.

A number of recent studies attempt to quantify the effects of GVC participation on economic growth. Kummritz et al. (2017) find that GVC integration generally increases an industry's value added, especially when participating in upstream stages. They additionally highlight the importance of country-specific characteristics and policy for benefitting from trade integration. Constantinescu et al. (2019) find that participation in GVCs is a significant driver of labour productivity in a set of 40 countries since 1995, in particular finding strong effects of the use of imported inputs in production for exports.[24] Lopez-Gonzalez (2016) also finds (short-run) positive effects from importing intermediates on a country's value added as well as on employment, in particular in services. Yet, these studies are based on datasets that are limited in the coverage of countries (mostly high- and middle-income countries) and/or time (from 1995 onwards). The aim of this chapter is to put the mixed-blessing hypothesis of GVC participation to the test using a wider set of countries, in particular including more lower-income countries, and for a longer time period, tracking development from 1970 onwards as GVC development has a much longer history (e.g., Gereffi, 1999).

A large and related literature has investigated FDI spillovers and arrives at a broad consensus in favour of positive productivity spillovers to industries that supply multinationals through backward linkages (Javorcik, 2014), with little evidence for other channels though (Iršova and Havránek, 2013). Collier and Venables (2007) argue that trade agreements that allow for specialisation in GVCs increase export competitiveness. They find that less developed countries especially benefit from preferential trade preferences with soft rules of origin, allowing for more fine-grained GVC specialisation. Sen (2019) finds that overall trade integration has a positive

[24] See also Kummritz (2016) on labour productivity effects.

impact on manufacturing employment in developing countries via the expansion of the scale of production. However, it has a negative impact via the productivity effect as less labour is needed per unit of output. Moreover, positive employment effects appear to peter out once domestic wages for unskilled workers start to rise, as follows from surplus-labour models in the vein of Arthur Lewis (Lewis, 1954; Sen, 2019). More qualitative studies on GVCs are in general critical about the opportunities for upgrading through GVC participation in the long run (Gereffi, 1994; Kaplinsky, 2000; Barrientos et al., 2016). They highlight governance structures with asymmetric power relationships between lead firms in advanced countries and suppliers from developing regions, such that firms are often locked in low-value activities (Humphrey and Schmitz, 2002). Escaping from such captive governance structures may only be possible under the right domestic conditions, such as well-functioning domestic innovation systems offering ample opportunity to absorb and assimilate new technologies (Pietrobelli and Rabellotti, 2011). Such demanding preconditions for success were present in South Korea and Taiwan in the past, but may not be in place in the average developing country today.

To investigate the mixed-blessing hypothesis, we introduce new measures of domestic value added and employment generated by exporting and relate them to GVC participation. The hallmark of GVC participation is specialisation in particular tasks in the production chain such that a country may only add part of the value of the exported good. In an already classic case study, Dedrick et al. (2010) find that China mainly performs assembly, testing and packaging activities on imported high-tech components in order to export high-end electronics, while relying on software, supply chain orchestration and branding from foreign companies. Following the seminal contribution of Hummels et al. (2001), we use a measure of vertical specialisation in trade as the main indicator for GVC participation, which is standard in this literature (e.g., Kummritz et al., 2017; Constantinescu et al., 2019). For outcome measurement, we measure *all* manufacturing value added and employment in a country that is generated in the production for exports, not only in the exporting industry, but also in upstream industries. Traditionally, studies (such as discussed above) focus only on growth in the industry or the firms that actually export. Yet, with production fragmentation other domestic firms might benefit through delivering inputs to the exporting firms. One might even argue that the establishment of backward linkages into the domestic sectors is a hallmark of success in benefitting from trade. This idea is far from new, going back at least to Hirschmann (1958) (see also Chenery et al., 1986), but until now the generation of employment in upstream stages of production has not been measured for a large set of countries over a long period. We study the period from 1970 to 2008 and analyse trends in up to 58 countries. We draw on disaggregated data from UNIDO's Indstat2 (2016) on manufacturing value added and employment (i.e., number of workers), and on national input-output tables from Pahl and Timmer (2019b).

In econometric analyses, we find robust evidence for a strong positive association of GVC participation with labour productivity growth in the export chain. This result is robust to different specifications and holds for subsets of developing countries. Moreover, this effect becomes larger the further a country is from the productivity frontier. This is found in analyses of 10-year periods, and we obtain qualitatively similar results in analyses of 5-year periods. In contrast, we do not find evidence for positive effects on employment growth. If anything, we find a negative association between GVC participation and employment growth for countries close to the productivity frontier. Hence, the results suggest that, on average, higher GVC participation is not necessarily associated with higher employment generation in manufacturing. This is in line with the mixed-blessing hypothesis.

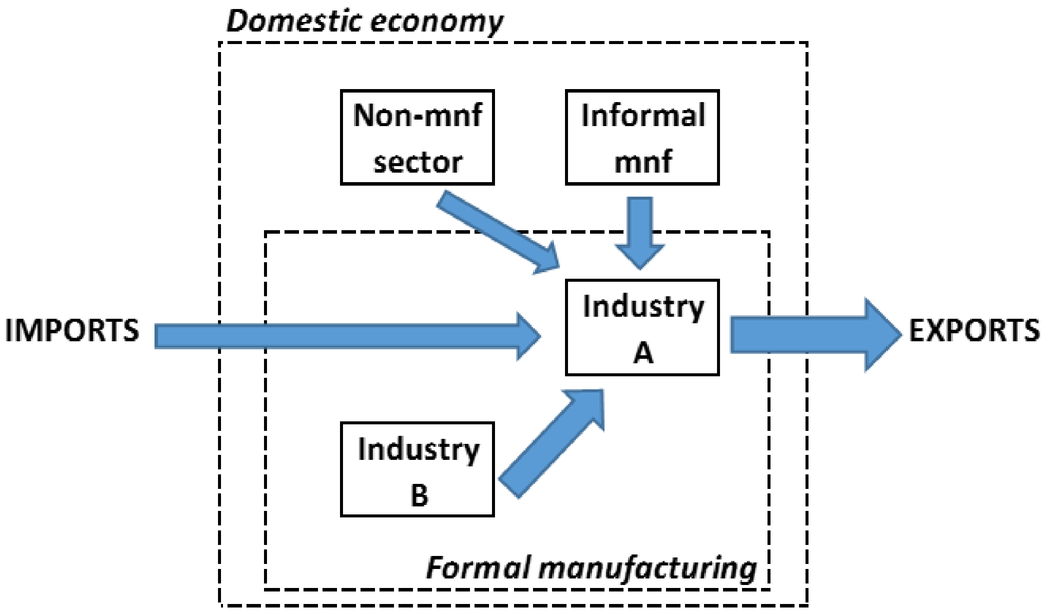
The rest of the chapter is organised as follows. In section 3.2, we outline the methodology to measure value added and employment in a country's exports. In section 3.3, we describe the data sources used, with additional detail in the supplementary material (3.7). In section 3.4, we econometrically relate our export performance measures to GVC participation, and we discuss results and robustness. Section 3.5 concludes.

3.2 Methodology

3.2.1 The concept of value added and employment in exports

With the emergence of GVCs, the economic effects of exporting become less visible, as they materialise not only in the exporting industry, but also in all other domestic industries that deliver intermediates, an old idea going back to at least Hirschmann (1958), see also Chenery et al. (1986). We illustrate this in Figure 3.1.

Figure 3.1 Domestic value chains in export production



Source: Authors' illustration.

Domestic value added in exports (and employment in exports) is a composite of domestic activities by several firms in multiple industries. Directly exporting firms in industry A generate value added by producing exports. The exported value however is also composed of value added that is generated by other domestic firms. This may include indirect contributions of firms within the exporting industry, but also contributions from firms in other industries. We distinguish for the purpose of this chapter between formal manufacturing (represented by industry B), informal manufacturing and non-manufacturing sectors. Those indirect contributions can be sizeable and depend on the strength of backward linkages to domestic firms.

To measure domestic employment and value added in exports we are using the value chains as opposed to generic industries as units of analysis. We define domestic value chains by the exporting industry (industry A in Figure 3.1). The domestic value chain includes all domestic direct and indirect contributions to these exports, but excludes the foreign content (imported intermediates).[25] Our analysis explicitly focuses on employment in formal manufacturing, arguably providing the most desirable jobs in terms of working conditions and

[25] Studies using firm-level data cannot account for these indirect contributions. Typically, importing and exporting firms themselves are considered but not their production linkages to other domestic firms (see Del Prete et al., 2017; Foster-McGregor et al., 2014; Okafor et al., 2017).

pay (see e.g. Rodrik, 2013). This is not to deny the importance of informal job creation, but foremost reflects the paucity of data on output and employment in the informal sectors. In our data, the share of these indirect formal manufacturing contributions reaches more than 40 percent in the upper decile of our sample.[26] This variation matters cross-sectionally and inter-temporally. In South Korea, for example, the share of indirect formal manufacturing employment to products exported by the automotive industry varies between 35 and 50 percent between 1970 and 2008.

3.2.2 The measurement of value added and employment in exports

The implementation is based on using information from input-output tables. We follow Koopman et al. (2014) and Los et al. (2016) and define the domestic value-added content in exports (VAXD) as:

$$VAXD = \mathbf{v}(\mathbf{I} - \mathbf{A_{dom}})^{(-\mathbf{1})}\ \mathbf{e} \tag{1}$$

where $\mathbf{v}$ is a row vector of value added to gross output ratios (i.e., value added per unit of output), $\mathbf{I}$ is an identity matrix, $\mathbf{A_{dom}}$ is a matrix of domestic input coefficients and $\mathbf{e}$ a column vector of exports. Multiplying the Leontief inverse $(\mathbf{I} - \mathbf{A_{dom}})^{(-\mathbf{1})}$ with the export vector $\mathbf{e}$ identifies how much output is generated in any sector of the economy to produce the export vector, that is, in all firms that are directly and indirectly exporting. Pre-multiplying with $\mathbf{v}$ identifies how much value added is generated in these sectors when producing the needed output. If instead pre-multiplied by a row vector of employment inputs to gross output ratios, the left-hand side captures how much employment is needed to produce the exports. We refer to this as employment in exports. Labour productivity in exports is defined as value added in exports divided by employment in exports. We can calculate these measures for exports originating from any manufacturing industry through appropriate choice of the export vector.

How to measure GVC participation of a country? We use a measure of vertical specialisation in trade which is standard in the literature by now, introduced by Hummels et al. (2001) and used, for example, in Kummritz et al. (2017) and Constantinescu et al. (2019). More specifically, our measure of GVC participation (G) is the imported input content in exports,

[26] The direct effect is value added and employment generated by exporting firms only. In input-output terms, we define it as the vector of value-added to gross output ratios times the export vector.

which is equal to gross exports (X) minus VAX-D (see Los et al., 2016). We express it as a share of gross exports, such that G is bound between zero and one:

$$G = (X - VAXD)/X \; . \tag{2}$$

A ratio close to one indicates that an exporting industry is relying heavily on imported intermediates and GVC participation is thus high, and vice versa.

This GVC participation measure is a so-called backward linkage indicator. It is particularly well-suited for analysing countries that initiate assembly activities based on imported parts and components, or put differently, that are active in downstream activities in the chain. It is less well-suited to trace the benefits of GVC participation for countries that are mostly involved in upstream activities that do not require sophisticated inputs, such as in early phases of processing natural resources or food. To this end, some studies have also used so-called forward indicators, which capture the share of an industry's value added that is used by other countries in production of their exports, see for example Baldwin and Lopez-Gonzalez (2015) and Kummritz et al. (2017). Kummritz et al. (2017) refer to this as integration in a GVC as a 'seller' rather than a 'buyer'. They stress the importance of knowledge spillovers that are not embodied or necessarily associated with the buying of inputs, such as those that arise from implementation of global standards or training supported by the global retail firms (e.g., Ivarsson and Alvstam, 2010). The calculation of this forward measure requires full inter-country input-output tables (rather than national tables), which are not available for a wide set of countries. Moreover, our focus is on growth in manufacturing industries rather than in natural resource industries, such as agriculture and mining. Yet, there might also be differences across manufacturing products. We explore this issue through splitting our sample according to the level of technological sophistication of the inputs used.

3.3 Data sources

To implement our methodology, we build a new dataset by combining two data sources: one on formal manufacturing employment and value added and one on national input-output tables. We obtain a dataset of 58 countries, of which 38 are developing countries as classified by the World Bank in 1990 (see Table 3.A1 in the appendix). For series of formal manufacturing employment and value added, we use UNIDO's Indstat2 (2016). This database provides data for a large set of developing countries over a long period and is therefore suited for our long-run analysis. Supplementary material section C provides a detailed description of the data construction and a summary table on each country. However, we would like to stress two points of relevance for interpreting our results here.

Firstly, the UNIDO data are collected from national industrial surveys and censuses, which are based on samples of manufacturing establishments. These surveys typically exclude small-scale and informal establishments. Depending on the survey, it might cover firms with at least five, or ten, *formally* employed workers. In many developing countries, the informal workforce makes up a large share of manufacturing employment, which is thus not covered in these surveys. We therefore stress that our results apply to the productivity and employment effects in formal manufacturing production. Rodrik (2013) points out that it is jobs in the modern sector of the economy that are missing in most low-income countries. Such jobs might be created anew through starting and expanding modern activities in a GVC, or they may arise due to transitioning of informal firms to formal status (see La Porta and Shleifer, 2008, who argue that the latter is not very common).

Secondly, the UNIDO data, nor national input-output tables, make a distinction between export-related production and production for domestic demand. This is because there is no separate information on input use by type of firm (exporting or not). It is generally found that exporting firms use greater shares of imports in production than firms that do not export (e.g. Koopman et al., 2012 on China and de Gortari, 2019 on Mexico), and they typically also have a higher labour productivity level. As we only have data on all firms in the industry, the first might lead to an underestimation of the GVC participation level in our approach, and the latter may lead to an overestimation of the level of employment in exports. Yet, in order to affect our regression results, there needs to be a particular bias in the *growth* rates of employment (as our dependent variable is in growth rates) and this bias must be systematically related to the *level* of GVC participation. While we do not rule out this possibility, we are not aware of any a priori reasons why this would be the case, as it will depend on the unknown covariation of changes in the productivity gap between exporters and non-exporters, and changes in their shares in overall industry employment. In any case, this measurement issue provides an important and more general caveat pertaining to any study that estimates the employment and value-added content of exports with input-output tables that do not distinguish between exporters and non-exporters. Further improvements in data for a large cross-section of countries on both fronts would need to be awaited.[27]

When using UNIDO's Indstat2 (2016), we need to apply harmonisation strategies. The data exhibit a large amount of gaps and changes of classifications, which make time-series comparisons erroneous and the data not readily usable. Value added is available at three different price concepts (in basic prices, in purchaser's prices and in an unknown price concept), and employment is available for two different measures (as persons engaged and as employees).[28] Our construction is therefore guided to maximise intertemporal (over time), internal (between variables), and international (cross-country) consistency. To assure intertemporal consistency, which is most important in the long-run productivity comparisons of this chapter, we apply linking procedures. After careful harmonisation and aggregation, we start with an initial cross-section of both variables and link a series of growth rates to the respective cross-section. Hence, we obtain the initial level from the raw data, but we are able to repair breaks from changes in revisions or classifications of activities by using trends in the different series. When constructing these growth rates, we fill gaps (e.g., due to lack of overlap) by additional data sources and assumptions, which we describe in the supplementary material.

Internal consistency between value added and employment is generally high as both variables come from the same type of sources, which are industrial censuses and surveys of the manufacturing sector. The initial values to which we link the series therefore come from the same year in both variables, yielding highest internal consistency. International consistency is most difficult to achieve, but it is also least critical in our analysis. We aggregate all variables to the same internationally comparable ISIC Rev.3.1 combinations, such that we cover in principle the same activities. Actual coverage of the industrial censuses may of course still differ (e.g., through different threshold levels of the minimum establishment size). As the dependent variable is in growth rates in the econometric analysis, this thus matters only if, for example, productivity growth in larger firms is different from smaller firms (which are not covered in all countries in the industrial surveys). It is also not possible to use the same classification of variables across all countries because some only report in basic prices and

[27] Bems and Kikkawa (2019) investigate the aggregation bias in macro data by comparing the GVC participation measure (vertical specialisation) as obtained from macro data (as used here) with one based on firm-level data. They find indeed relatively large differences for China and Vietnam, as expected. Yet, they find only small differences for the remaining countries, namely for Belgium, Chile, India, Indonesia, Korea and Latvia.

[28] Ideally, one would like to have hours worked as the measure of labour input. Data on hours worked is notoriously hard to find, in particular for low-income countries.

others only in market prices. We can control for a large part of such cross-country differences by including dummies. Country dummies account for level differences that arise from different price concepts, and capture systematic differences in growth rates related to establishment size. SM Table 3.5 in the supplementary material provides a more detailed overview, indicating the covered years and underlying sources.

For the input-output tables, we rely on Pahl and Timmer (2019b), which construct a time series of national input-output tables for 91 countries since 1970. Importantly, this dataset provides estimates of $\mathbf{A_{dom}}$ and $\mathbf{e}$, required to implement equation 1. The industry detail is 14 manufacturing industries and 5 broad non-manufacturing sectors. Details on this data source are provided in the supplementary material of chapter 2 in this thesis, but we repeat key characteristics here. The series of our 58 countries are based on *annual* data of trade flows, value added and output at a detailed industry level and final demand totals. Importantly, value added to gross output ratios are a key ingredient when constructing input-output tables, as they pin down intermediate use in an industry. Annual variation in those is often not achieved for developing countries at the level of detailed manufacturing industries. Using UNIDO's Indstat2 (2016), however, fills this gap.[29] Those series of trade flows and production data are combined with benchmark input-output tables to construct time series of $\mathbf{A_{dom}}$. In the process, the import matrix is obtained by the conventional proportionality assumption (after identifying intermediates). That is, it is assumed that imported products are used in the same way as domestically produced products.

A last important issue pertains to the fact that all value data discussed so far is in nominal US$. To study developments over time, one needs to account for price developments that may vary greatly across different types of outputs and inputs (e.g., prices of raw materials have shown large swings over the studied period). To account for such price effects, we follow Rodrik (2013) and add time period-industry dummies in all our regressions. This is based on the assumption that traded products follow the law of one price (and we are only considering exported products). The necessary assumption is that dollar inflation terms are industry-specific and do not vary across countries (except for an idiosyncratic random error term). Hence, we can write growth of real labour productivity in exports of industry i in country c over period t

[29] Note that in chapter 2, UNIDO's Indstat is used as an estimate to split the total (formal and informal) manufacturing sector. In this chapter, output and value added from UNIDO are directly used because we focus on formal manufacturing. Differences in the obtained variables are generally small.

as $\widehat{lp_{ict}^{real}} = \widehat{lp_{ict}^{nom}} + \pi_{it} + \varepsilon_{ict}$, where *nom* indicates nominal (dollar) labour productivity, π_{it} is the inflation term of products in industry i over period t and ε_{ict} is the idiosyncratic error term. As can be seen, industry-time period dummies absorb the inflation term and thereby control for price effects. This holds as long as exported manufactured products face common world price trends, and the independent variables in the regression (see equation 3 below) are not systematically correlated to deviations from this world price trend.

3.4 Empirical results

We investigate the relationship between GVC participation and growth of employment and labour productivity in long-run periods at the level of individual value chains. We identify chains by the country-industry that exports, so in total there are 754 (58 countries with 13 industries).[30] Our dataset covers an unbalanced panel over the period 1970 to 2008. To focus on long-term developments, we use three 10-year periods going backward from 2008, and one 8-year period 1970 to 1978. For each country-industry, we thus observe up to four periods.

To explore the relationship, we rank our observations by level of GVC participation at the beginning of each period pooled across country-industries and time periods. We define the top quartile of these observations as the group with 'high GVC participation' and the bottom quartile as the group with 'low GVC participation'. In Table 3.1, we present one-sided t-tests for differences in means of labour productivity and employment growth between the two groups. The group with 'high GVC participation' appears to have higher growth rates of labour productivity, but not of employment. The mean of labour productivity growth is 0.067 for observations with low GVC participation, and 0.073 for observations with high GVC participation in the full set of countries. In the subset of developing countries, it is 0.055 and 0.080 respectively. These differences in means are statistically significant, as shown in Table 3.1, especially for developing countries. For employment, however, there is much weaker evidence for a relationship. Table 3.1 shows the means of the two distributions, which are 0.051 for low and 0.049 for high participation in the set of all countries. For developing countries, value chains with low GVC participation also experience faster growth of employment: 0.077 (low) against 0.071 (high). These differences are not statistically significant however. Taken

[30] We exclude ISIC Rev.3 industry 23, 'Coke, refined petroleum and nuclear fuel'. It appears to be an important outlier. Apart from statistical concerns, another reason to exclude it is its large dependency on oil, which exhibits highly volatile prices (see also section SM B).

together, these results suggest that higher GVC participation might contribute positively to labour productivity growth, but not to employment growth.

Table 3.1 Difference in means: average annual growth rates in 10-year periods

	Low GVC participation Mean	High GVC participation Mean	t-value	p-value
All countries				
Growth of labour productivity in exports	0.067 (N=522)	0.073 (N=522)	1.55	p<0.10
Growth of employment in exports	0.051 (N=522)	0.049 (N=522)	0.28	p>0.10
Developing countries only				
Growth of labour productivity in exports	0.055 (N=288)	0.080 (N=288)	4.61	p<0.01
Growth of employment in exports	0.077 (N=288)	0.071 (N=288)	0.62	p>0.10

Note: 'High GVC participation' are all observations in the top quartile of the respective distribution of the GVC participation index. 'Low GVC participation' are all observations in the bottom quartile of the distribution. There are 57 countries of which 37 are developing ones: Argentina, Bangladesh, Brazil, Bulgaria, Chile, China, Colombia, Cyprus, Czech Republic, Ecuador, Egypt, Estonia, Greece, Hungary, India, Jordan, Kenya, Latvia, Lithuania, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Rumania, Russia, Saudi Arabia, Senegal, Slovakia, Slovenia, South Africa, South Korea, Sri Lanka, Thailand, Turkey, Uruguay.
Source: Authors' calculation on described dataset.

3.4.1 Econometric model

To investigate the issue in full, we estimate the following model:

$$\widehat{lp}_{ict} = \beta_0 + \beta_1 G_{ic,t-10} + \beta_2 lp_{ic,t-10} + \beta_3\left(lp_{ic,t-10} \times G_{ic,t-10}\right) + C_c + T_{it} + \varepsilon_{ict}, \tag{3}$$

where *i* is exporting industry, *c* is country, *t* is time period and ε is the error term. In the baseline model, the time periods are 10 years and $\widehat{lp}$ is accordingly growth of labour productivity in exports over these 10 years. All independent variables are measured at the start of each time period (indicated by *t-10*, depicting the start of the respective period). The main variable of interest is GVC participation, measured by our participation index and abbreviated by *G*. Following Rodrik (2013), we add time period-industry dummies T_{it} to account for price developments.[31] We also add country dummies, C_c, to control for country-fixed effects. These may include potential cross-country differences in the measurement of value added and employment as described in section 3.3. They also pick up effects due to country-size differences, since it is well known that larger countries tend to have lower GVC participation because more intermediates are domestically available (e.g., Baldwin and Lopez-Gonzalez, 2015; Timmer et al., 2013).

We also add the nominal labour productivity level (lp) at the beginning of each period as an explanatory variable. As all our regressions include time period-industry dummies, lp is measured relative to the global productivity frontier (which varies only by industry and time period). As shown in Rodrik (2013), patterns of unconditional convergence are strong in manufacturing. Lagging countries can benefit from the availability of information and codified knowledge, which helps them to learn from earlier innovations and thus catch up. Our specification identifies whether there is any additional effect of participating in GVCs beyond an unconditional trend of convergence. Countries that engage in GVCs might additionally benefit, for example, from direct production assistance and use of sophisticated inputs embodying technology. We also add an interaction term (lp x G) to study whether the effect of GVC participation depends on the distance to the productivity frontier. We would expect that the productivity effects operate especially in value chains where the productivity level is further from the productivity frontier, since this might offer more scope for learning.

We use cluster-robust standard errors to control for heteroscedasticity. Errors are clustered at the cross-sectional identifier, that is, the country-industry dimension. All our independent variables are in log-terms. We run regressions for long 10-year periods as well as for shorter medium-run 5-year periods (section SM B), following the same regression set up.

Our model for explaining employment growth follows a similar set-up. The full model is given by:

$$\widehat{emp}_{ict} = \beta_0 + \beta_1 G_{ic,t-10} + \beta_2 lp_{ic,t-10} + \beta_3 \left(lp_{ic,t-10} \times G_{ic,t-10}\right) + \beta_4 Reg_{c,t-10} + \beta_5 Hum_{c,t-10} + T_{it} + \varepsilon_{ict}, \tag{4}$$

[31] Value added is in nominal dollars and we assume that the inflation term is only product (and not country) specific by the law of one price for internationally traded products (see section 3.3).

where $\widehat{emp}$ is growth of employment in exports. Again, all independent variables are measured at the beginning of each time period (indicated by *t-10*, depicting the start of the respective period). We add time period-industry dummies to control for fluctuations in world demand. For example, world demand for 'automotives' might develop differently than demand for 'food and beverages' and thus affect employment growth in these value chains. We also add human capital (*Hum*) and regulatory institutions (*Reg*) as additional control variables at the country-level, based on the following arguments summarised, for example, in Sen (2019). There is a large literature arguing that stricter labour market regulations may have detrimental effects on employment generation. For example, labour market regulations may create adjustment costs to which firms may respond by reducing labour demand (Heckman and Pages, 2004). Furthermore, labour market regulations may increase the bargaining power of workers, potentially reducing investments and the scale of production (Besley and Burgess, 2004). If true, we can expect a negative association with employment growth in exports. We measure labour market institutions by a component of the Index of Economic Freedom (Fraser Institute, 2015). As the detailed index of labour market regulations is not available for a large set of countries before 1980, we use a more aggregate component for all periods. This component broadly captures 'regulation' and also includes measures on the business and credit market environment. It is available every 5-years and we therefore linearly interpolate between these years to obtain measures at the beginning of each studied period.[32]

We also include an indicator for the level of human capital (*Hum*). A highly skilled workforce may imply a comparative advantage in skill-intensive activities (Wood and Berge, 1997). For developing countries, this might imply specialisation in manufacturing activities as opposed to primary production within the manufacturing value chains and thus might have a positive effect on manufacturing employment growth (for a similar argument, see Sen, 2019). However, it could also imply a shift towards capital-intensive production if skilled labour and capital are complements in the production process (in the spirit of, e.g., Acemoglu and Pischke, 1998). We obtain human capital stock at the country level from PWT9.0 (Feenstra et al., 2015). This index is a combination based on the average years of schooling from Barro and Lee (2013) and an assumed rate of return to education from Psacharopoulos (1994).

[32] We have also obtained the measure of labour market rigidities by Campos and Nugent (2018), which is available for 5-year intervals. Our results on GVC participation and on the other variables do not change. Using this variable, we find that labour market rigidities are negatively correlated to employment growth. However, these data are not available for Cyprus and Hungary (only recent years) of our covered countries.

We also add labour productivity. We might expect that value chains closer to the productivity frontier have slower employment growth, because these value chains are more likely to be substituting away from labour to capital, following the lead of more developed countries that typically specialise in more capital-intensive activities as wages rise. On the other hand, high relative labour productivity might also signal low unit labour costs and allow countries to capture a larger share of world demand, increase the scale of production and generate employment growth. We also investigate whether the effect of GVC participation depends on the distance to the productivity frontier by inclusion of an interaction term between participation and labour productivity. One might expect that only countries far from the productivity frontier benefit from participation as they specialise in labour-intensive production stages when engaging in GVCs, while developed countries offshore labour-intensive stages and attract capital-intensive ones.

Lastly, we also present all specifications with country dummies to control for the country averages in the participation index and measurement differences. Adding country dummies might further be useful to control for (time-invariant) wage differences across countries. Lower wages might make it easier to attract labour-intensive production stages and thus yield employment growth. Explicitly controlling for wages is difficult, as wages are only rarely systematically collected and therefore not available for a broad set of countries and industries over a long time period.

Summary statistics of our main variables are given in Table 3.2.

Table 3.2 Summary statistics: 10-year periods

Variable	Obs.	Mean	SD	Min	Max
Growth of employment	2,088	0.05	0.11	-0.67	0.95
Growth of labour productivity	2,088	0.07	0.06	-0.18	0.38
Labour productivity level (ln)	2,088	9.34	1.12	5.61	12.71
GVC participation (ln)	2,088	-1.55	0.60	-3.63	-0.28
Human Capital	2,088	2.41	0.53	1.19	3.52
Regulatory institutions	2,088	6.09	1.12	2.15	8.44

Source: Authors' calculation based on described dataset.

We would further like to stress that our results show associations between GVC participation and economic outcomes, rather than causal effects. In particular, the regression set-up is potentially plagued by reverse causality. High productivity growth, for example, may be the pre-requisite for integration into GVCs. We partly address this issue by using the level of GVC participation at the beginning of each period and correlate it to the subsequent growth of labour productivity. However, this only partially addresses the problem in case labour productivity growth is serially correlated. For this reason, we strictly refrain from stating any causal relationships.

3.4.2 Main results

We begin by discussing the results on labour productivity growth in exports. Table 3.3 shows the regression results for our long-run (10-year) periods. Without any controls (except the time period-industry dummies), we find a strong positive and significant relationship between GVC participation and labour productivity growth (column 1). A 1-percent increase in the GVC participation index is associated with a 0.010 percentage point higher growth rate. This implies a 0.8 percentage-point increase in the growth rate if a chain increases its participation from the 25th to the 75th percentile in our sample. In column 2, we add dummies to account for country-fixed effects. The coefficient almost doubles and is still statistically distinguishable from zero. A 1-percent increase in GVC participation is associated with a 0.019 percentage-point increase in the growth rate, implying a 1.5 percentage-point increase from the 25th to the 75th percentile of GVC participation.

In columns 3 and 4, we add initial labour productivity level in exports and the interaction with GVC participation. Consistent with Rodrik's (2013) finding on convergence, the effect of initial labour productivity is negative and statistically different from zero (for all levels of GVC participation). The coefficient of GVC participation is positive, while the coefficient on the interaction is negative. This suggests that the effect of GVC participation is stronger for countries that are further from the productivity frontier. To show this, we graph the marginal effects of the changes in the participation index by different levels of labour productivity for the result of column 3 in Figure 3.2. It shows that the effect of GVC participation is positive and significantly different from zero for all value chains with labour productivity (ln) lower than or equal to 10, which is the 69th percentile of our sample. For the least productive country-industries in our sample, the coefficient increases up to 0.034 implying a rise in labour productivity growth of 2.6 percentage points when increasing participation from the 25th to the 75th percentile in our sample, holding everything else constant. The estimated effect is not significantly different from zero for observations with labour productivity larger than 10, and turns significantly negative for countries with initial labour productivity (ln) of 11.5. This corresponds approximately to the top 1 percent of our sample. This strongly suggest an association between GVC participation and labour productivity growth in long-run periods, especially in chains further from the productivity frontier.

Table 3.3 GVC participation and labour productivity in exports growth

Dependent variable: Growth of formal manufacturing labour productivity in exports								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Baseline		Interaction: labour productivity		Developing countries	Interaction: Asia	Industry heterogeneity	Including non-manufacturing
GVC participation (ln)	0.0104***	0.0198***	0.0733***	0.0566***	0.0214***	0.0139**	0.0328***	0.0282***
	(0.00191)	(0.00370)	(0.0148)	(0.0151)	(0.00497)	(0.00545)	(0.00741)	(0.00617)
Labour productivity (ln)			-0.0249***	-0.0650***				
			(0.00263)	(0.00367)				
GVC Participation x labour productivity			-0.00706***	-0.00559***				
			(0.00154)	(0.00164)				
GVC participation x Asia						0.0225***		
						(0.00730)		
GVC participation x light Mfg							-0.00985	
							(0.00789)	
GVC participation x resource-based Mfg							-0.0156**	
							(0.00690)	
Constant	0.138***	0.185***	0.356***	0.694***	0.167***	0.152***	0.158***	0.171***
	(0.00783)	(0.0183)	(0.0257)	(0.0323)	(0.0233)	(0.0234)	(0.0234)	(0.0277)
Observations	2,088	2,088	2,088	2,088	1,152	1,152	1,152	992
Countries	57	57	57	57	37	37	37	24
Adjusted R-squared	0.341	0.530	0.395	0.660	0.461	0.466	0.463	0.481
Time period-industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors to heteroscedasticity in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All independent variables are measured at the beginning of each period. Columns 5 to 7 are based on the sample of developing countries, as defined by income status in 1990 (see Table 3.A1). Asia is a dummy that is one for all East and South-East Asian countries. Industry dummies in column 7 are described in the text. Non-manufacturing in column 8 is included for a subset of countries, as described in the main text.

Source: Authors' calculation based on described datasets.

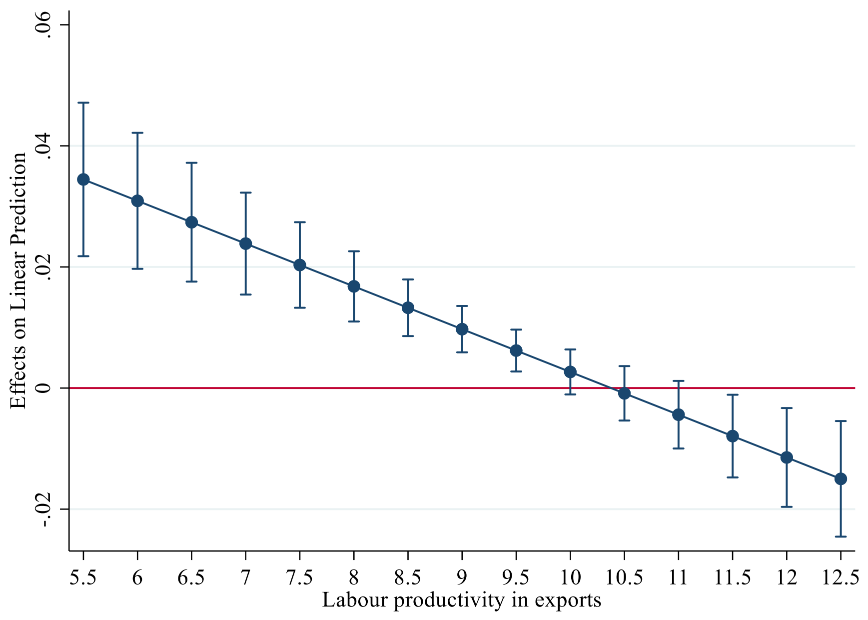
Table 3.4 GVC participation and employment in exports growth

	Dependent variable: Growth of formal manufacturing employment in exports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Baseline		Interaction: labour productivity		Developing countries	Interaction: Asia	Industry heterogeneity	Including non-manufacturing
GVC participation (ln)	-0.00398	-0.00102	0.0849***	0.0813***	-0.00239	0.000807	0.00149	-0.0116
	(0.00392)	(0.00758)	(0.0286)	(0.0312)	(0.0102)	(0.0120)	(0.0149)	(0.0108)
Labour productivity (ln)			-0.0136***	0.0140				
			(0.00500)	(0.00950)				
GVC Participation x labour productivity			-0.00958***	-0.00870***				
			(0.00288)	(0.00335)				
Human capital			-0.0572***					
			(0.00634)					
Regulatory environment			-0.000104					
			(0.00185)					
GVC participation x Asia						-0.00954		
						(0.0149)		
GVC participation x light Mfg							-0.0121	
							(0.0165)	
GVC participation x resource-based Mfg							-0.00225	
							(0.0153)	
Constant	0.0265*	0.0151	0.282***	-0.0875	0.0127	0.0191	0.0156	0.0313
	(0.0139)	(0.0267)	(0.0547)	(0.0778)	(0.0403)	(0.0420)	(0.0421)	(0.0418)
Observations	2,088	2,088	2,088	2,088	1,152	1,152	1,152	992
Countries	57	57	57	57	37	37	37	24
Adjusted R-squared	0.080	0.215	0.142	0.225	0.178	0.177	0.177	0.210
Time period-industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors to heteroscedasticity in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All independent variables are measured at the beginning of each period. Columns 5 to 7 are based on the sample of developing countries, as defined by income status in 1990 (see Table 3.A1). Asia is a dummy that is one for all East and South-East Asian countries. Industry dummies in column 7 are described in the text. Non-manufacturing in column 8 is included for a subset of countries, as described in the main text.

Source: Authors' calculation based on described datasets.

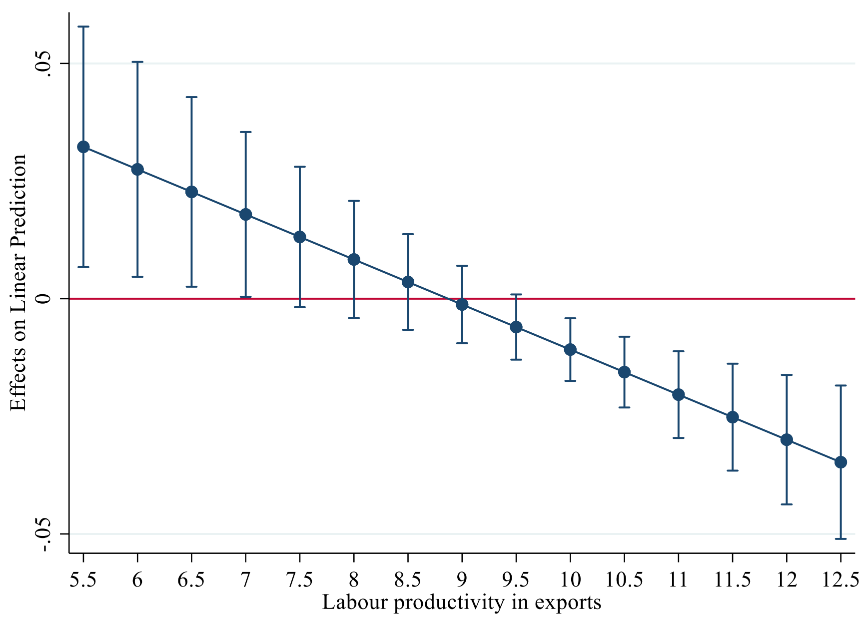
Figure 3.2 Marginal effects of GVC participation on labour productivity growth, by levels of labour productivity in exports



Note: Marginal effects are obtained from regression of Table 3.3, column 3. Confidence interval for 95%.

Source: Authors' calculation.

Figure 3.3 Marginal effects of GVC participation on employment growth, by levels of labour productivity in exports



Note: Marginal effects are obtained from regression of Table 3.4, column 3. Confidence interval for 95%.

Source: Authors' calculation.

We next investigate the relation between GVC participation and employment growth. Results are given in Table 3.4 (all specifications include time period-industry dummies). Our baseline regression indicates that employment growth in exports appears not to be associated with GVC participation. The estimated coefficient is small in magnitude and not different from zero (column 1), and is even closer to zero when adding country dummies (column 2). This is in strong contrast with our findings on labour productivity growth and confirms the t-tests in Table 3.1. In columns 3 and 4, we add the interaction with labour productivity. In column 3, we also add country-level control variables, which we drop in column 4 when we add country dummies, as the controls vary only little over time. Of our control variables in column 3, human capital is significantly (negatively) associated with employment growth. This negative association might be because of a complementarity between high-skilled workers and capital. Availability of skills might yield a shift to more capital-intensive methods of production and thus reduce employment.

In both columns 3 and 4, the sign of the coefficient of GVC participation is positive, and the sign of the interaction is negative, suggesting a similar relationship as for labour productivity. Figure 3.3 shows the marginal effects based on column 3. It suggests that the association turns significantly positive for the very least productive value chains with lower labour productivity (ln) than 7. Yet, this constitutes less than 2 percent of our sample. We find, however, that it is significantly negative for value chains with labour productivity (ln) larger than about 9.5, which corresponds to about 45 per cent of our sample. In conclusion, these results show that there is no strong positive association between GVC participation and employment growth in exports. If anything, GVC participation is even associated with slower employment growth for relatively productive value chains.

In the supplementary material (SM B), we provide two robustness tests on these results. In the baseline regressions, we introduce time period-industry dummies to control for world price trends (see section 3.3). An additional way of addressing this issue is by excluding intermediate inputs that are particularly affected by volatile prices, as this might affect our measure of GVC participation. We show results based on alternative measures of GVC participation that exclude the use of intermediates with highly volatile prices (mining products and petroleum). For labour productivity, the association based on these alternatives is somewhat lower than in our baseline regression, but it remains highly statistically significant and larger for countries further from the productivity frontier. In terms of employment growth, the estimates are similar in size to the results in the baseline regression and also not statistically different from 0. Secondly, we run all regressions for shorter 5-year periods. The relationship to labour productivity is qualitatively similar but somewhat stronger. On employment, the estimated coefficients tend to be lower, and we find a negative association on average.

Our results differ from Lopez-Gonzalez (2016), who finds positive effects from GVC participation on employment in exports. He studies employment at the level of one aggregated manufacturing sector, 11 services sectors, agriculture and mining. Hence, while our approach zooms into formal manufacturing employment in manufactured exports, his result might reflect more on the employment possibilities outside manufacturing, in particular in services exports, which are more important for richer countries. Overall, our results clearly show that, on average, higher GVC participation is not positively associated with employment growth in manufacturing. This result generalises Formai and Caffarelli (2016), who also study formal manufacturing. Their approach is not based on country-specific input-output data but they exploit variation in a country's import share of intermediate imports interacted with an industry's propensity to source (based on the 1997 US input-output table). Yet, the authors also find positive productivity effects but no employment effects from GVC participation for a set of 50 countries for one period between the 1990s and the 2000s.

3.4.3 Extensions

We further investigate several avenues to explore heterogeneities of the main result of positive productivity but limited employment gains.

Country heterogeneity.

We firstly explore heterogeneities across country groups. In Table 3.3, we report in column 5 results for developing countries only (non-high income in 1990, see Table 3.A1). The point estimate is positive and statistically different from zero and is slightly larger in magnitude than in column 2. This suggests that developing countries are particularly benefitting from GVC participation (consistent with the result on distance to the productivity frontier). In column 6, we add an interaction with a dummy that is one for all countries located in East and South-East Asia. We find a statistically significant difference for Asian countries, and the coefficient is more than twice as large. One might argue that Asian countries are engaged differently in GVCs compared to other regions. Asian countries might be engaged as buyers of sophisticated intermediate goods, while other regions might be more engaged as upstream suppliers and therefore benefit less from backward GVC participation. Further, one might argue that the geographic region makes it suitable for benefitting from GVC participation due to embeddedness in the global production hub ‘factory Asia’ (e.g., Baldwin and Lopez-Gonzalez, 2015). Strong linkages across countries at different stages of development may offer easy access to sophisticated inputs and opportunities to take over production stages as wages rise in the relatively more developed countries (in the spirit of the flying geese model). Gereffi (1999) illustrates these dynamics within Asia for the textile industry, showing how production shifted from Japan in the 1950s to South Asia around 2000. With lacking regional production hubs, other developing countries still import intermediates, but might potentially experience less learning through cooperation in a dense network of producers.

In columns 5 and 6 of Table 3.4, we repeat the exercise for employment growth. We find that the average association for developing countries only is not statistically different from zero, and the point estimate is close to zero, as in column 2 for the full set of countries. In column 6, we show the interaction with the Asia dummy. Yet, even for this group of countries with the strongest productivity gains, we do not find a positive association with employment growth. While these countries benefit through productivity growth and possibly through rising value and output generation, this does not seem to translate into employment growth on average. The main results of productivity gains, but limited employment gains even hold for this set of countries.

In the supplementary material SM Table 3.1, we further explore heterogeneity across other groups. We firstly explore differences of developing countries that have successfully transitioned to higher income status. We add an interaction with a dummy that is one for all countries that have transitioned to high-income status in 2008 (zero otherwise; column 3), and an interaction with a dummy that is one for all countries that transitioned to any higher income category between 1990 and 2008 (zero otherwise; column 4). The estimates suggest that the positive effect of GVC participation is not only limited to the countries that have generally developed successfully, as the estimates for transitioning countries are not statistically different from the remaining set of countries. In column 5, we add an interaction with a dummy that is one for all countries that capture on average 5% of GDP or more from oil revenues between 1970 and 2008 (zero otherwise; World Bank, 2018a). These oil-dependent countries may participate differently in GVCs (e.g., through forward linkages by selling raw materials), such that gains from GVC participation as a buyer are potentially smaller. The point estimate for this group is indeed smaller but not statistically different from the remaining set of non-oil dependent countries.

We repeat this exercise for employment in SM Table 3.1.B. We find that the average association of GVC participation to employment growth is statistically more positive in the successful countries that transition to higher income status since 1990 (column 4). The estimated coefficient for these transitioning countries is about 0.01 (adding the coefficient for the baseline and the interaction), which however is not statistically different from zero (test results not reported).

Industry heterogeneity.

We further explore heterogeneities across exporting industries. GVC participation as measured in this study may be potentially more relevant in industries, in which we expect stronger backward spillovers. To this end, we attempt to classify exporting industries by sophistication of used intermediates. The general idea is that, if a less developed country imports sophisticated materials and components to be assembled locally, this may activate learning, for example through embodied knowledge. In contrast, assembly of simple inputs or raw materials may generate much less learning and the upgrading potential might arise from cooperation with global buyers rather than from importing. We classify industries of machinery (ISIC Rev.3 29), electronics (30t33) and transport equipment (34t35) as chains using relatively sophisticated intermediates. The remaining exporting industries with less sophisticated intermediate use are split between light manufacturing, that is, food (15t16), textiles (17t18), leather (19), wood (20), paper and printing (21t22) and manufacturing not elsewhere classified (36t37); and resource-intensive, that is, chemicals (24), rubber (25), non-metallic minerals (26), and metals (27t28).

There is no standard classification of industries according to intermediate input use, but we can take leads from the literature. Yeats (1998) firstly distinguished trade of parts and components from trade of primary inputs using trade data. He argued that the former is more relevant for trade in production networks (see also Gaullier et al., 2019). In a similar vein, Rauch (1999) distinguished the differentiation of industries by whether the products are reference priced, sold on organised exchange or neither. This classification mainly speaks to distinguishing primary inputs from more sophisticated parts and components (consumer goods are hardly reference priced). We deem our classification to be broadly consistent with these ideas, but acknowledge that this is a matter of degree and further research is required in this regard.

In column 7 of Table 3.3, which is also based on the set of developing countries, we add interactions of GVC participation with dummies for the exporting industries with less sophisticated inputs and light manufacturing, and for resource-based industries (high sophistication is the baseline group). We indeed find a strong effect for the set of industries with sophisticated intermediate use, which is larger than the average across all industries in column 5. The interaction terms show that the association between GVC participation and labour productivity growth is particularly lower in the resource-based exporting industries. The point estimate is also lower in the light-manufacturing industries than in the high-sophistication industries, but this difference is not statistically significant. The association within all groups of industries is still statistically different from zero. This finding indeed points to additional benefits from GVC participation, suggesting that industries with sophisticated intermediate input use offer more scope for upgrading. Nonetheless, it suggests positive productivity gains across all three groups. In SM Table 3.2 in the supplementary material, we further show these results for the full set of countries. We also find positive correlations in all three groups of industries but we do not find statistical differences across the groups, while the ranking of the point estimates is similar.

In column 7 of Table 3.4, we repeat the exercise for employment growth. We also find the largest coefficient in magnitude for the set of sophisticated industries, but we do not find statistical differences across the groups. In all three groups, the association is not statistically different from zero. Hence, even in the group of industries in which we find the strongest association to productivity growth, we do not identify a positive relation with employment growth. The same holds in the set of all countries (SM Table 3.2). In further (non-reported) regressions, we estimated the specification with industry dummies for each exporting industry individually. Also for specific individual industries, we do not find average positive associations with employment. We can interpret this with regard to the main hypothesis in that the bias against labour is widespread across all groups of industries. As productivity grows, it appears that the scale of production is not sufficiently increasing to generate additional employment.

Including non-manufacturing.

Our chapter focusses on the labour productivity and employment effects in formal manufacturing. However, in column 8 of Tables 3.3 and 3.4, we explore employment generation including indirect contributions by non-manufacturing. Manufacturing firms may not be able to generate jobs as technology is biased against labour but possibly jobs are created outside manufacturing with strong linkages to manufacturing.

Besides, by focusing on manufacturing, a possible concern is that one might understate employment growth in exports if outsourcing is pervasive. If a firm chooses to specialise in its core activity and outsources non-core activities to other domestic *non-manufacturing* firms (most likely to services), a focus on manufacturing understates the growth rate. This is relevant if this implies substantial changes in growth rates (i.e., the phenomenon is sizeable) and if it is systematically related to GVC participation. One might indeed argue that firms in countries with high GVC participation at the beginning of the period continue to seek their comparative advantage and therefore specialise in more narrow activities. In this case, our results on employment growth would be downward biased. Yet, this only affects our results for outsourcing to non-manufacturing because we use chains as our units of observation (not separate industries), and jobs outsourced to other manufacturing industries will thus be picked up by our employment measure. Secondly, it is not clear that the phenomenon of outsourcing (to services) is indeed an important issue in developing countries, as we are not aware of studies that systematically document and track this phenomenon in developing countries (on developed countries, see Crozet and Milet, 2017; Kelle, 2013).

To explore these issues, we turn to additional data on the other sectors in the economy. We add data from the GGDC 10-Sector Database (10SD; de Vries et al., 2015) that covers employment for broad sectors in ISIC Rev.3 since the 1960s. We expand our employment accounts by information on broad sectors from that database, but use UNIDO’s Indstat for manufacturing industries (to keep it consistent with our value-added accounts, and as the 10SD only provides total manufacturing). The value-added accounts for broad sectors are consistent, as they are based on national accounts in both sources. The employment data of the 10SD is mainly obtained through population censuses and therefore covers all economic activities (formal and informal). In combination, this yields a dataset of 24 countries (17 developing).

We estimate the (total) employment content in exports, and the respective labour productivity in exports. For labour productivity growth (column 8, Table 3.3), the estimated coefficients are relatively large compared to column 2, but the set of countries is much smaller than in our baseline results and not directly comparable. The baseline regression for this smaller set of countries for formal manufacturing shows quantitatively similar results as in column 8 (coefficient equals 0.0278). In terms of employment (column 8 of Table 3.4), we find a negative coefficient but it is not statistically different from zero. Again, this coefficient is not directly comparable to column 2 and the estimated coefficient for this smaller set of countries for formal manufacturing is -0.0001 (also not statistically different from zero). We also find qualitatively similar results for the set of developing countries only (not reported). Hence, taking non-manufacturing aboard does not alter our main conclusion of productivity gains, but limited employment growth. Job generation outside manufacturing also does not seem to be faster in country-industries that participate more in GVCs.

3.5 Conclusion

It is sometimes argued that GVCs provide a quick way to industrialise without the need for building up a sizeable domestic manufacturing base first. Countries supposedly benefit from specialisation in carrying out particular stages in global production networks, realising long-run productivity and employment growth by gradually moving up the value chain. In this study, we investigate whether GVC participation is indeed a possible panacea for weak industrialisation trends in the South. The key contribution of our study is to provide long-run econometric evidence on the impact of GVC participation on economic upgrading using data since 1970 on a large set of developing countries.

We find robust evidence for a positive productivity effect from stronger GVC integration. Moreover, and in line with Rodrik (2013), we find that relatively less productive countries can benefit more from GVC participation in terms of productivity growth as they are further away from the technology frontier. This speaks against concerns that GVC participation is likely to leave developing countries locked in unproductive activities (see Dalle et al., 2013). Countries become more productive in performing the same activities through product and process upgrading or might move into higher value-adding activities, generally referred to as functional upgrading (Gereffi, 1999). Our measurement framework does not distinguish between these scenarios, and this is an interesting avenue for further research. There is a need for further characterisation of activities in GVCs such as R&D, fabrication or marketing activities which differ in their factor requirements and the potential for knowledge spillovers. Reijnders and de Vries (2018) and Timmer et al. (2019) provide new evidence on functional specialisation based on (cross-country) data on occupations, inspired by the seminal work on business functions of Sturgeon and Gereffi (2009).

Our findings on employment generation in the formal manufacturing sector provide a more pessimistic outlook than for productivity growth. We do not find evidence for a positive relation between GVC participation and employment growth, even after conditioning on various other determinants, neither for 10-year periods nor for shorter 5-year periods. We find some weak evidence in favour of positive effects for the poorest countries, but these wear out closer to the productivity frontier and turn significantly negative at productivity levels characteristic for middle-income countries.

We conclude that GVC participation is a mixed blessing at best: on average stimulating productivity growth but not employment growth. We hypothesise, in the vein of Rodrik (2018), that this is due to bias against (unskilled) labour in modern technologies that are diffusing throughout GVCs, driven by stringent requirements from multinational lead firms in the chains.

We would like to stress a number of caveats to our findings. First, we focus on the *formal* manufacturing sector and do not study the impact of GVC participation on employment generation outside the formal sector. For example, formal manufacturing firms might outsource particular labour-intensive tasks to households and micro firms with irregular and informal workers (on India, e.g., Moreno-Monroy et al., 2014). One might even argue that the success of the formal sector in exporting and productivity growth depends crucially on its ability to exploit networks of informal workers (Gereffi, 2014). Given lack of reliable data on irregular employment, we have no way of testing this. We focus on formal firms as it is organised work that is ultimately needed for operating the scale and technologies of modern industrialisation. Moreover, working conditions and pay are generally better than in irregular and informal jobs. Another potential employment spillover lies in the outsourcing of services by formal manufacturing. There is limited systematic evidence on the extent and in particular on the rise of services outsourcing in developing countries. In additional exploratory analysis, we find no evidence of job creation when we include indirect non-manufacturing in relation to GVC participation. It is an interesting avenue for future research relating to the broader debate on the role of business services in structural change over the course of development (e.g., Lavopa and Szirmai, 2018).

Another caveat is the possible wedge between labour productivity and (real) wage growth. Bernhardt and Milberg (2013) and Bernhardt and Pollak (2016) argue that the latter is more relevant from a welfare perspective. Correlation between the two is strongly positive in the medium to long-run, but not necessarily in the short-run, in particular in countries with labour markets characterised by surplus labour in the vein of Lewis (1954), see also Sen (2019). It also raises the question of the governance structure and the bargaining power of firms involved in GVCs, as these are prime determinants of the distribution of income across the GVC participants (Strange and Humphrey, 2019).

Lastly, while we were able to expand the set of lower income countries in our analysis, and trace their development over a longer period, there is still scope to expand coverage. This is particularly true for the least developed countries in Africa and Asia, which are typically not covered as the analysis puts high demands on the data (such as detailed employment statistics and input-output data). It might be that they experience upgrading dynamics in GVCs that are different from the relatively richer developing countries analysed in this study. In particular resource-rich countries are likely to engage differently in GVCs as forward suppliers, relying more on market knowledge and access spillovers from MNE buyers and less on spillovers in the use of sophisticated inputs (e.g., Ivarsson & Alvstam, 2010; Havranek & Irsova, 2011).

More generally, we like to emphasise that our cross-country study should be seen as a complement to country case studies that do more justice to the large heterogeneity across sectors and countries, and the important idiosyncrasies in countries' institutional settings. In particular, our findings do not rule out that some countries have successfully relied on GVC production as a stepping stone for both productivity and employment creation. China and Thailand, for example, have both successfully developed through GVC participation (Wad, 2009; Kee and Tang, 2016). Gereffi and Sturgeon (2013) argue that such success depends on new and GVC-specific industrial policies. The authors emphasise the developmental role of local firms serving multiple multinational lead firms at the same time, the so-called 'global suppliers'. They suggest that countries must attract such global suppliers to generate employment and to allow local firms to have access to world-class inputs through domestic sourcing of global suppliers. We find that Asian countries have benefitted in particular from GVC participation, which may indeed be due to their nurturing of sophisticated suppliers and the development of regional supply networks (Coe and Yeung, 2015). Critical in the assessment is whether the conditions for success are in reach today for developing countries that are typically small and cannot built from a base supported by buoyant domestic demand. More generally, Rodrik (2018) advocates close cooperation between public and private entities to identify and evaluate the bottlenecks to generating linkages between the highly productive (exporting) firms and the rest of the economy. Kummritz et al. (2017) have explored policy-related correlates that matter for generating value added. We believe it is an important future avenue to explore similar correlates in terms of employment and labour productivity. Case-study approaches are well-suited to suggest and refine hypotheses on why a particular country deviates positively or negatively from the average. We conclude that economic upgrading through GVC participation is possible, but far from automatic.

3.6 Appendix: additional table

Table 3.A1. List of countries

Country	Income level	10-year periods N	10-year periods T	5-year periods N	5-year periods T	Country	Income level	10-year periods N	10-year periods T	5-year periods N	5-year periods T
Argentina	LM	26	2	52	4	*Kuwait*	H	52	4	89	7
Australia	H	26	2	39	3	*Latvia*	UM	13	1	26	2
Austria	H	52	4	91	7	*Lithuania*	UM	13	1	26	2
Azerbaijan	LM	-	-	13	1	*Malaysia*	LM	52	4	91	7
Bangladesh	L	36	3	73	6	*Mexico*	UM	26	2	52	4
Belgium	H	52	4	91	7	*Morocco*	LM	39	3	78	6
Brazil	UM	13	1	26	2	*Netherlands*	H	52	4	91	7
Bulgaria	LM	13	1	26	2	*New Zealand*	H	13	1	26	2
Canada	H	52	4	91	7	*Norway*	H	52	4	91	7
Chile	LM	52	4	91	7	*Peru*	LM	13	1	39	3
China	L	26	2	65	5	*Philippines*	LM	52	4	91	7
Colombia	LM	52	4	91	7	*Poland*	LM	52	4	91	7
Cyprus	H	39	3	78	6	*Portugal*	UM	52	4	91	7
Czech Rep.	LM	13	1	26	2	*Romania*	LM	13	1	26	2
Denmark	H	52	4	91	7	*Russia*	UM	13	1	26	2
Ecuador	LM	49	4	89	7	*Saudi Arabia*	UM	13	1	26	2
Egypt	L	52	4	89	7	*Senegal*	LM	8	1	24	2
Estonia	UM	13	1	26	2	*Singapore*	H	52	4	91	7
Finland	H	52	4	91	7	*Slovakia*	LM	13	1	26	2
France	H	52	4	91	7	*Slovenia*	UM	13	1	26	2
Germany	H	13	1	39	3	*South Africa*	UM	26	2	65	5
Greece	UM	13	1	26	2	*South Korea*	UM	52	4	91	7
Hungary	UM	52	4	91	7	*Spain*	H	52	4	91	7
India	L	52	4	91	7	*Sri Lanka*	L	26	2	65	5
Ireland	H	52	4	91	7	*Sweden*	H	52	4	91	7
Israel	H	52	4	91	7	*Thailand*	LM	52	4	91	7
Japan	H	52	4	91	7	*Turkey*	LM	52	4	91	7
Jordan	LM	25	2	63	5	*Uruguay*	UM	50	4	89	7
Kenya	L	35	3	72	6	*USA*	H	52	4	91	7

Note: Income level is the World Bank income classification of 1990 (or closest available year). H is high income, UM is upper middle, LM is lower middle, L is low income. N is the number of observations, T is the number of time periods covered, shown for the respective dataset with 10 and 5-year periods.

3.7 Supplementary material: robustness and data construction

SM A. Additional Tables

SM Table 3.1. GVC participation and economic outcomes, country heterogeneity.

SM 3.1.A. Labour productivity

Dependent variable: Growth of formal manufacturing labour productivity in exports						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
GVC participation (ln)	0.0136***	0.0214***	0.0225***	0.0182**	0.0220***	0.0139**
	(0.00301)	(0.00497)	(0.00554)	(0.00727)	(0.00529)	(0.00545)
GVC participation x High-income 2008			-0.00453			
			(0.00776)			
GVC participation x Transition 2008				0.00585		
				(0.00727)		
GVC participation x Oil					-0.00488	
					(0.0102)	
GVC participation x Asia						0.0225***
						(0.00730)
Constant	0.124***	0.167***	0.169***	0.173***	0.168***	0.152***
	(0.0117)	(0.0233)	(0.0242)	(0.0229)	(0.0237)	(0.0234)
Observations	1,152	1,152	1,152	1,152	1,152	1,152
Countries	37	37	37	37	37	37
Adjusted R-squared	0.230	0.461	0.461	0.461	0.461	0.466
Time period-industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	Yes	Yes	Yes	Yes	Yes

Note: see SM 3.1.B.

SM Table 3.1.B. Employment

Dependent variable: Growth of formal manufacturing employment in exports						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
GVC participation (ln)	-0.00166	-0.00239	0.00147	-0.0190	-0.00374	0.000807
	(0.00642)	(0.0102)	(0.0108)	(0.0147)	(0.0106)	(0.0120)
GVC participation x High-income 2008			-0.0153			
			(0.0174)			
GVC participation x Transition 2008				0.0304**		
				(0.0152)		
GVC participation x Oil					0.0106	
					(0.0282)	
GVC participation x Asia						-0.00954
						(0.0149)
Constant	0.0650**	0.0127	0.0220	0.0434	0.00976	0.0191
	(0.0260)	(0.0403)	(0.0408)	(0.0398)	(0.0412)	(0.0420)
Observations	1,152	1,152	1,152	1,152	1,152	1,152
Countries	37	37	37	37	37	37
Adjusted R-squared	0.107	0.178	0.177	0.180	0.177	0.177
Time period-industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	No	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors to heteroscedasticity in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All independent variables are measured at the beginning of each period. High-income is a dummy for all developing countries that reach high-income status in 2008. Transition is a dummy for all developing countries that transition to higher income group. Oil is a dummy for all countries that generate 5% of GDP or more from oil revenues. Asia is a dummy for all countries in East and South-East Asia.
Source: Authors' calculation based on described datasets.

SM Table 3.2. GVC participation and economic outcomes, industry heterogeneity.

	Dependent variable: Growth of formal manufacturing labour productivity in exports		Dependent variable: Growth of formal manufacturing employment in exports	
	(1)	(2)	(3)	(4)
VARIABLES	Full sample	Developing countries	Full sample	Developing countries
GVC participation (ln)	0.0242***	0.0328***	0.00544	0.00149
	(0.00501)	(0.00741)	(0.00938)	(0.0149)
GVC participation x light Mfg	-0.00382	-0.00985	-0.00954	-0.0121
	(0.00482)	(0.00789)	(0.00908)	(0.0165)
GVC participation x resource-based Mfg	-0.00610	-0.0156**	-0.00759	-0.00225
	(0.00426)	(0.00690)	(0.00875)	(0.0153)
Constant	0.182***	0.158***	0.0126	0.0156
	(0.0182)	(0.0234)	(0.0276)	(0.0421)
Observations	2,088	1,152	2,088	1,152
Countries	57	37	57	37
Adjusted R-squared	0.530	0.463	0.215	0.177
Time period-industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Note: Robust standard errors to heteroscedasticity in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All independent variables are measured at the beginning of each period. Industry dummies as described in the text.
Source: Authors' calculation based on described dataset.

SM B. Robustness

As indicated in section 3.3, price development might be a concern for our estimation. In the baseline regressions, we introduce time period-industry dummies to control for world price trends. An additional way of addressing the issue is by excluding intermediate inputs that are particularly affected by volatile prices. This is of particular interest as GVC participation is measured as the share of foreign value added in exports. If prices of specific intermediates rise, countries that import those products will show relatively higher GVC participation and countries that produce those domestically will show relatively lower GVC participation. To provide a check on this, we use two alternative measures of GVC participation that exclude intermediates of the broad sector mining and electricity (ISIC Rev.3 C and E), and of 'refined petroleum' (23). Two sectors that are arguably most prone to volatile prices.

We firstly follow Hummels et al. (2001) by setting all imports of the respective sectors to 0 and recalculate the measure of GVC participation. This implicitly assumes that the respective imports are produced domestically. By definition, this first alternative GVC participation measure is smaller than the original one in all countries but closer to the original one in countries that produce those products domestically (i.e., resource-abundant ones). Secondly, we construct our own alternative GVC participation measure by setting imports and domestic production of the two sectors to 0, and then recalculate domestic and foreign value added in exports. The sum of both is a hypothetical export value excluding any value from mining/electricity and refined petroleum. By construction, these hypothetical export values are smaller than the original values. We then recalculate our measure of GVC participation, which thus depicts the share of foreign value added in exports if production did not use any of the excluded products. These shares are smaller than the original ones if the country is using relatively more domestic than imported intermediates of the two sectors (i.e., in resource-abundant countries), and vice versa.

We show the results in SM Table 3.3 in columns 1 and 2 for labour productivity and in columns 3 and 4 for employment. Columns 1 and 3 use our own alternative and columns 2 and 4 follow Hummels et al. (2001). For labour productivity, the association based on these alternatives is indeed somewhat lower than in our baseline regression. Yet, the association remains highly statistically significant. In terms of employment growth, the estimates are close to the result in the baseline regression and economically close to and statistically not different from 0. In unreported results, we also find qualitatively similar results including the interaction with labour productivity (as in columns 3 and 4 of Table 3.3 and 3.4), and if we limit the set of countries to developing countries only (column 5 of Table 3.3 and 3.4).

We perform a second robustness check by splitting our sample in 5-year periods instead of 10-year periods. While our focus is on the longer 10-year periods, we explore whether we find differences by length of period. In SM Table 3.4, we present the main regression results for 5-year periods (5-year steps between 1971 and 2006). We repeat the baseline regressions in columns 1 and 2 for labour productivity and in 3 and 4 for employment. Overall, the coefficients for labour productivity are larger but show the same qualitative relationship. On employment, this is also true while the estimated coefficients tend to be lower. The average association is negative and statistically different from zero (column 3). We further run all regressions of the extensions discussed in section 3.4.3 in 5-year periods, finding qualitatively similar results (not reported). It overall suggests that our result of positive productivity but limited employment gains, obtained for 10-year periods, can similarly be concluded from 5-year periods.

SM Table 3.3. GVC participation and economic outcomes, alternative measurement

	Dependent variable: Growth of formal manufacturing labour productivity in exports		Dependent variable: Growth of formal manufacturing employment in exports	
	(1)	(2)	(3)	(4)
VARIABLES	Excluding mining/oil	Excluding mining/oil (HIY)	Excluding mining/oil	Excluding mining/oil (HIY)
GVC participation (ln)	0.0150***	0.0120***	0.00250	0.00637
	(0.00348)	(0.00349)	(0.00703)	(0.00692)
Constant	0.171***	0.163***	0.0250	0.0361
	(0.0179)	(0.0179)	(0.0255)	(0.0253)
Observations	2,088	2,088	2,088	2,088
Countries	57	57	57	57
Adjusted R-squared	0.526	0.524	0.215	0.216
Time period-industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Note: Robust standard errors to heteroscedasticity in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All independent variables are measured at the beginning of each period. In columns 1 and 4, GVC participation is based on an alternative specification excluding domestic and foreign mining/electricity and refined oil intermediates. In columns 2 and 5, GVC participation is based on an alternative specification treating foreign mining/electricity and refined oil intermediates as domestic (following Hummels et al., 2001).
Source: Authors' calculation based on described dataset.

SM Table 3.4. GVC participation and economic outcomes, 5-year periods

	Dependent variable: Growth of formal manufacturing labour productivity in exports		Dependent variable: Growth of formal manufacturing employment in exports	
VARIABLES	(1)	(2)	(3)	(4)
GVC participation (ln)	0.0405***	0.0897**	-0.0204**	0.00135
	(0.00635)	(0.0365)	(0.00929)	(0.0439)
Labour productivity (ln)		-0.0892***		0.00826
		(0.00673)		(0.0110)
GVC participation x labour productivity		-0.00797*		-0.00202
		(0.00430)		(0.00474)
Constant	0.386***	0.860***	0.0970*	0.0700
	(0.0290)	(0.0546)	(0.0503)	(0.0902)
Observations	3,877	3,877	3,877	3,877
Countries	58	58	58	58
Adjusted R-squared	0.377	0.492	0.147	0.147
Time period-industry Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Note: Robust standard errors to heteroscedasticity in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All independent variables are measured at the beginning of each time period.

Source: Authors' calculation based on described datasets.

SM C. Time series of formal manufacturing employment and value added

In this section, we describe the data construction of the series of formal manufacturing employment and value added. Our dataset covers an unbalanced sample of 58 countries of which 38 are non-high-income countries (see Table 3.A1).

The construction of the series of employment and value added relies mainly on the UNIDO Industrial Statistics database (UNIDO Indstat2, 2016). In some cases, these data are complemented by other sources to bridge small gaps in the data. As described in the main text, the construction is guided to maximize intertemporal (over time), internal (between variables), and international (cross-country) consistency by applying linking procedures. We proceed as follows.

In the first step, we clean the data. We set observations to missing which we identify as erroneous entries. Firstly, we set all negative entries of value added and employment to missing. Secondly, we treat zeros and missing observations. In the raw data, zeros might appear when data is missing, that is, when the industry is not sampled in the respective year. It can, however, also indicate that the actual value is zero.[33] We therefore set zeros to missing that (i) are entered in-between recorded values. Hence, if an industry has a positive value in year 1, a zero in year 2, but a positive value in year 3, we assume that the zero in-between is a missing value. We set observations to missing if (ii) the industry records zeros at the beginning or end of the time series, but emerges from 0% to more than 5% of total manufacturing, and vice versa. Hence, we allow for the possibility that industries emerge or vanish, but restrict it to a change of 5% in total manufacturing. We assume that larger changes from or to zero indicate missing data. We do not set observations to missing if only zeros are recorded in one industry, and thus allow for the possibility that some industries do not exist at all. We also set observations to missing if (iii) a positive value is recorded in the other variable. For example, if employment data is recorded, but value added is reported as zero, we treat the zero as a missing value.

Having obtained the cleaned value added and employment data, we aggregate into the 14 ISIC Rev.3 categories: 15t16, 17t18, 19, 20, 21t22, 23, 24, 25, 26, 27t28, 29, 30t33, 34t35, 36t37. We additionally construct aggregate categories for 17t19 and 29t33, because almost all countries report the categories 18t19 and 29t30 together in years before the 1990s, such that we cannot aggregate into our classification. This provides aggregated series of 14 industries plus the two higher aggregates of value added and employment in three and two different

[33] A motivating example for this treatment is Senegal. Between 1986 and 1989, no industry records any value added and employment except for recycling and food manufacturing. After this period, all remaining industries start recording again. It is very unlikely that all industries disappear in the same year and return in the same year.

classifications, respectively. Value added is reported in basic prices, in market prices and in unreported classification; employment as persons engaged and employees. To bridge gaps within these five series, we linearly interpolate the series. If the two more aggregated categories are available but not the disaggregated ones, we use the closest available split to obtain the disaggregated categories. Per country, we obtain up to five series for the two variables, aggregated to the 14 manufacturing industries.

We use these aggregated data to obtain initial cross-sections for both variables. To assure international consistency, we take the latest available value added cross-section in basic prices and employment cross-section as employees. If these classifications are not available, we prefer value added in basic prices over market prices over unreported classification, and employment as employees over persons engaged. Both cross-sections come from the same year to assure internal consistency.

We extrapolate these cross-sections backward and forward by growth-rate series, which we construct as follows. Firstly, starting from the aggregated data, we calculate the growth rates within each of the variable-classification series, that is, of up to five series per country. Secondly, we combine these series into one single series of growth rates for each of the two variables. We thus assume that the growth rates are consistent across different classifications. When combining these growth rates into one single series, we prefer growth rates in basic prices over market prices over unreported classification. For employment, we prefer the series in employees over the series in persons engaged.[34] These constructed growth rates account for almost all derived data points in our data.

Next, we complement these series with additional sources and assumptions to bridge small gaps, for example, if there is no overlap between series in different classifications. Firstly, we add data from the OECD (OECD, 2017). This database provides total (formal and informal) manufacturing employment for up to 17 manufacturing industries. We use this data source to backdate and extrapolate, and to bridge gaps in our series of formal manufacturing employment and value added. By using this data source, we assume that the growth rates of total manufacturing are consistent with the growth rate of formal manufacturing. For France and South Korea, we also add data from KLEMS (Jäger, 2017; ASIA KLEMS, 2017), and proxy the growth rates following the same assumption. We further bridge the remaining small gaps of mostly single years, but of up to four years, by assuming a common trend of labour productivity growth across manufacturing industries. This is only done if there is no overlap

[34] This procedure assures that we always start the extrapolation with growth rates of the same classification as the initial cross-section.

between two classifications of value added, which could not be repaired by the additional data sources. It occurs in 14 countries. SM Table 3.5 provides an overview of the data sources and time period coverage for each of the individual countries.

Legend for SM Table 3.5.

	Meaning
1	Growth rates are based on raw data
a	Growth rates are based on raw data, but use of higher aggregates 17t19 and/or 29t33 for respective industries
i	Growth rates for one or more industries are obtained from linear interpolation between raw data points
o	Growth rates for one or more industries are obtained from OECD (2017)
k	Growth rates for one or more industries are obtained from KLEMS
m	Growth rates of VA are based on common manufacturing trend of value added per worker
E	Employment classified as employees
PE	Employment classified as persons engaged
B	Value added classified in basic prices
M	Value added classified in market prices
NR	Value added classification is not reported

Note that the classification is not indicated in SM Table 3.5 if the cross-section for extrapolation is after 2008. All of those countries report employment as employees, except Uruguay (reporting persons engaged). All countries report value added in basic prices, except Cyprus, India, Jordan, Kuwait, Mexico and Peru (in market prices), and Japan, Russia and Uruguay (in unreported classification).

SM Table 3.5. Overview of sources by country

		70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08
ARG	EMP															1a	1a	1a	1a	1a	1a	1a	ia	ia	1	1	1	1	1	1	1	1	1	**E**	o	o	o	o	o	o
	VA															1a	1a	1a	1a	1a	1a	m	m	m	1	1	1	1	1	1	1	1	1	**M**	o	o	o	o	o	o
AUS	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**																		
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**B**																		
AUT	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	1	1	1	1	1i	1i	1i	1i	1i	1	1i	1i	1i	1i	1	1i	1i	1i
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	m	1	1	1	1	1	1i	o	1	1	1	1	1i	1i	1i	1i	1	1i	1i	1i
AZE	EMP																																1	1	1	1	1	1	1	1
	VA																																1	1	1	1	1	1	1	1
BEL	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1iao	iao	iao	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1	1	1	1	1	1	1	1	1	1	1	1	1	1
BGD	EMP							1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	1	i	i	1	i	i	i	i	i	i	i	1i	i	i
	VA							1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	m	m	m	1m	i	i	1	i	i	i	i	i	i	i	1i	i	i
BGR	EMP																										ia	1i	1	1	1	1	1	1	1	1	1	1	1	1
	VA																										iao	1a	1	1	1	1	1	1	1	1	1	1	o	1
BRA	EMP																										1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	iao	1
	VA																										1ao	1	1	1	1	1	1	1	1	1	1	1	1	1
CAN	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**M**	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CHL	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**M**	1i	1ao	1ao	1ao	1ao	1iao	1iao	1iao	1iao	1iao	1iao	1iao	1iao	1ao
CHN	EMP											1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	**E**	1
	VA											1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	o	1	1	1	1	**M**	o
COL	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	o	1	1	1	1	1	1	1	1	1
CYP	EMP			1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1				
	VA			1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1				
CZE	EMP																										1	1	1	1	1	1i	1	1	1	1	1	1	1i	1
	VA																										1	1	1	1	o	1	1	1	1	1	1	1	1i	1
DEU	EMP																										1	1	o	1	1	1	1	1	1	1	1	1	1	1
	VA																										o	o	o	1	1	1	1	1	1	1	1	1	1	1
DNK	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	i	1	**E**	1i	1i	1i	1i	1i	1i	1i	1i	1i
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	ia	1	1	1	1	**B**	1i	1i	1i	1i	1i	1i	1i	1i	1i
ECU	EMP	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1i	1	1	1	1	**E**
	VA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1i	1	1	1i	1	1	1	1	**M**
EGY	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**	ia	ia	ia	ia	ia	ia	ia	1	1	i	i	i	1	i	1	1i	1	i	i
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1ia	1a	1a	1a	1a	1a	1a	**B**	1a	1a	1a	1a	1a	1a	1a	1	1	i	i	i	1i	i	1i	1i	1	ia	ia
ESP	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EST	EMP																								1	1	1	1	1	1	1	1i	1i	1	1	1	1	1	1i	1
	VA																								1	1	1	1i	1	1	o	1	1	1	1	1	1	1	1i	1
FIN	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**E**	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	ia	ia	ia	ia	ia	1	1	1	1	1	1i	1	1	1	1	1	1	**B**	1
FRA	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1i	1i	1i	1i	1i	1i	1	1	1	1i	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	m	1a	1a	1a	1a	1a	1a	1a	1a	1a	m	1k	1k	1k	1ik	1k	1k	1	1	1	1i	1	1	1	1	1	1	1	1	1
GRC	EMP																								1	1	1	1	1	1	i	i	i	i	1	1	1	1	1	1
	VA																								1	1	1	1	1	1	i	i	i	i	1	1	1	1	1	1
HUN	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	1i	1i	1i	1i	1	1	1i	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1ia	1a	1ia	1a	1ao	o	1	1	1i	1	1	1	1	1	1	1	1

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SM Table 3.5 (continued). Overview of sources by country

		70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88
IND	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
IRL	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
ISR	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
JOR	EMP											1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA											1ia	1a	1a	1a	1a	1a	1a	1a	1a
JPN	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
KEN	EMP			1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA			1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
KOR	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
KWT	EMP	1a	1a	1a	1a	1a	1a	1a	ia	ia	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
LKA	EMP										1a	1a	**E**	ia	ia	ia	ia	ia	ia	ia
	VA										1a	1a	**B**	ia	1a	ia	ia	ia	1a	1a
LTU	EMP																			
	VA																			
LVA	EMP																			
	VA																			
MAR	EMP							1a	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia
	VA							1a	1ia	1ia	1ia	1ia	ia	ia	ia	ia	ia	ia	ia	ia
MEX	EMP															1a	1a	1a	1a	1a
	VA															1a	1a	1a	1a	1a
MYS	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
NLD	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	ia	ia	ia	ia	ia	ia
NOR	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
NZL	EMP	1a	1a	1a	ia	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**			
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**M**			
PER	EMP													1a	1a	1a	1a	1a	1a	1a
	VA													1a	1a	1a	1a	1a	1a	1a
PHL	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
POL	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
PRT	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1ia	1a	1a
ROU	EMP																			
	VA																			
RUS	EMP																			
	VA																			
SAU	EMP																			
	VA																			

		89	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08
IND	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	ia	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	o	1	1	1	1	1	1	1	1	1	1	1
IRL	EMP	1a	1a	1ia	1ia	1ia	1ia	**E**	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1a	1ia	1ia
	VA	1a	1a	1i	1i	1i	1i	**B**	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i	1i
ISR	EMP	1a	1ia	1ia	1ia	1ia	1ia	1ia	1ia	**E**	1ia	1ia	1ia	1ia	1ia	1ia	ia	ia	ia	ia	ia
	VA	1a	1a	1a	1a	1a	1a	1a	1a	**M**	o	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a
JOR	EMP	1a	1a	1a	1a	1a	ia	1	1i	1i	1i	i	1i	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1	1	1i	1i	1i	1	1	1i	1i	1	1	1	1	1	1
JPN	EMP	1a	ia	ia	ia	ia	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KEN	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1ia	**PE**	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia
	VA	1a	1a	1a	1ia	1ia	1ia	1ia	1a	1a	**B**	1	1	1	1	1	1	1	1	1	1
KOR	EMP	**E**	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	**M**	k	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KWT	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1
LKA	EMP	ia	ia	ia	ia	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	ia	ia	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	ia	ia	ia	1	1	1
LTU	EMP							1i	1i	1	1	1	1	1	1	1	1	1	1	1	1
	VA							o	o	o	o	o	1	1	1	1	1	1	1	1	1i
LVA	EMP					1i	1i	1i	**E**	1i	1i	1	1	1	1	1	1	1	1	1	1
	VA					1	1i	1	**B**	1io	1io	1io	1io	1io	1io	1io	1io	1io	1io	1io	1io
MAR	EMP	1ia	1ia	1ia	ia	ia	ia	ia	ia	ia	ia	ia	1	1	1	1	1	1	1	1	1
	VA	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	1	1i	1i	1	1	1i	1i	1	1
MEX	EMP	1	1i	1i	1i	1i	i	i	i	i	i	i	i	i	i	1	i	i	i	i	1i
	VA	1	1i	1i	1i	1i	1	1	1	1	1	1	1	1	1	1i	1i	1i	1i	1i	1i
MYS	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	**E**	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	**B**	o	1	1	1	1	1	1	1	1
NLD	EMP	1a	1a	1a	1a	1a	1a	1	1	1i	1i	1	1i	1	1i	1i	1i	1i	1	1	1
	VA	ia	ia	ia	ia	ia	ia	1	1	1	1	1	1	1	1	1	1	1	1i	1	1i
NOR	EMP	1a	1a	1	1	1	1i	1i	1i	1i	1i	1	1i	1i	1i	1i	1	1	1	1i	1i
	VA	1a	1a	1	1	m	1	1	1i	1i	1i	1i	1i	1i	1i	1i	1	1	1	1i	1i
NZL	EMP																				
	VA																				
PER	EMP	1a	1a	1a	1a	ia	1a	1	1	i	i	i	i	1	1	**PE**					
	VA	1a	1a	1a	1a	ia	m	1	1	i	i	i	i	1i	1i	**NR**					
PHL	EMP	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	i	1	i	1	i	1	1	i	1
	VA	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	i	1	i	1	i	1	1	i	1
POL	EMP	1a	1a	1a	1	1	1	1	1	1	1	1	1	1i	1i	1	1	1	1	1	1
	VA	1a	1a	1a	1	1	1	o	1	1	1	1i	1i	i	1i	1	1	1	1	1	1i
PRT	EMP	1a	ia	ia	ia	ia	ia	ia	1	1	1	1	1	1	1	1	1i	1i	1i	1i	1i
	VA	1a	1a	1a	1a	1a	1a	o	1	1	1	1	1i	1	1	1	1i	1i	1i	1i	1i
ROU	EMP							1	1	1	1	1	1	1	1	1	1	**E**	1	1	1
	VA							1o	1o	1o	1o	1o	1o	1o	o	1ao	1	**B**	1ao	1ao	1iao
RUS	EMP								1	1	1	1	1	1	1	1	1	1	1	1	1
	VA								1	1	1	1	i	1	1	1	1	1	1	1	1
SAU	EMP							ia	ia	ia	ia	ia	ia	1ia	1ia	1ia	1ia	1ia	**E**	1	1
	VA							o	o	o	o	o	o	o	1iao	1iao	1iao	1iao	**NR**	o	o

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SM Table5 (continued). Overview of sources by country

		70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08
SEN	EMP																			ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	1	1	1	1	**E**						
	VA																			1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	1ia	**M**						
SGP	EMP	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	ia	1	1	1	1	**E**	1	1	1	1	1	1	1	1	1i	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	**B**	o	1	1	1	1	1	1	1	1i	1	1	1	1
SVK	EMP																								1	1	1	1	1	**E**	1	1i	1	1	1i	1i	1i	1i	1i	i
	VA																								1	m	1	1	1	**B**	1	1i	1	1	1i	1i	1i	1i	1i	1i
SVN	EMP																							1a	1a	1a	1i	1i	1i	1i	1i	1	1	1	1i	1	1	1	1	**E**
	VA																							1a	1a	m	1o	1o	1o	1o	1o	1i	1i	1i	1i	1	1	1i	1i	**B**
SWE	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1	1	1	1	1	1i	1	1	1	1	1	1	1
THA	EMP	1a	1a	ia	ia	1a	1a	1a	1a	ia	1ia	ia	ia	1a	ia	1a	ia	1a	ia	1a	1a	1ia	1a	ia	1a	1a	ia	1	i	**E**	i	1	i	1	i	i	i	1	i	I
	VA	1ia	ia	ia	ia	1a	1a	1a	1a	ia	1ia	ia	ia	1a	ia	1a	ia	1a	ia	1a	1a	1ia	1a	ia	1a	1a	ia	1	i	**M**	o	o	i	1	i	i	i	1	i	I
TUR	EMP	1a	1a	ia	ia	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	m	1	1	1	1	1	1	1	1	1	o	1	1	1	1	1	1	1
URY	EMP	ia	ia	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	ia	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1i	1i	1i	1i	i	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1	1	1	1	1i	1i	1i	1i	i	ia	1
USA	EMP	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**	ia	1	1	1	1	1	1	i	1	1	1	1	1
	VA	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**B**	o	o	1	1	1	1	1	1	1	1	1	1	1
ZAF	EMP										1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**E**	1a	ia	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	VA										1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	1a	**B**	m	ia	1i	i	i	1i	i	1i	1o	1o	1o	1o	1o	1o	1o	1o	1o	1o

Note: 1 indicates that at least one industry’s growth rate is based on raw data; a indicates that industries 17t18 and 19, and/or 29 and 30t33 are based on an aggregate split of the raw data; i indicates that at least one industry’s growth is based on linear interpolation; o indicates that at least one industry’s growth is based on data from OECD; k indicates that at least one industry’s growth is based on KLEMS data; m indicates that at least one industry’s value added growth is based on aggregate trend of value added per worker.